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A dynamic route guidance system based on real traffic data

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Abstract

Mobility is one of the vital goods of modern societies. One way to alleviate congestion and to utilise the existing infrastructure more efficiently are Advanced Traveller Information Systems (ATIS). To provide the road user with optimal travel routes, we propose a procedure in two steps. First on-line simulations supplemented by real traffic data are performed to calculate actual travel times and traffic loads. Afterwards these data are processed in a route guidance system which allows the road user an optimisation with regard to individual preferences. To solve this multiple criteria optimisation problem fuzzy set theory is applied to the dynamic routing problem.

Keywords: Traffic; Simulation; Fuzzy sets; Decision support systems; Advanced traveller information system

1. Introduction

Oversaturated freeways and congested arterial roads in cities reflect the fact that the road networks are not able to cope with the demand of mobility which will further increase in the near future. Meanwhile, Avanced Traveller Information Systems (ATIS) are developed, which offer optimal travel routes to road users with regard to the actual traffic state (e.g., [4]) in order to increase the efficiency of private car travelling.

The basic requirement for such recommendations is precise information about the actual traffic state, e.g., link travel times and traffic densities. These data are generated by simulations which use on-line measurements stemming from inductive loops as input. On the basis of these results, travel routes can be calculated and optimised. In general, road users have individual preferences while choosing a traffic route, e.g., travel time, route length, travel comfort, and road type. From the scientific point of view, this is a multiple criteria optimisation problem which can be solved for instance by symmetric optimisation.

The outline of the paper is as follows: In the next section, the used traffic flow model, road network and database are introduced and discussed. The following section describes the optimisation problem and the application of fuzzy set

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theory to the routing problem and its results. We close with a summary and a discussion.

2. On-line simulation

The basic idea of on-line simulations is as follows: *Local traffic counts serve as input for traffic flow simulations to provide network-wide information*. Therefore, we first introduce the traffic flow model. In the following subsections, we describe our study area and the database we employed.

2.1. Cellular automaton traffic flow model

Recently, the modelling and prediction of traffic flow became an important subject of research (e.g., [12]). In general, traffic flow models should describe the relevant aspects as simply as possible by keeping track of the essentials. A very simple traffic flow model is the cellular automaton model proposed by Nagel and Schreckenberg [7]. Since it is by design well-suited for large-scale computer simulations, it is possible to simulate road networks like the Autobahn network of Germany in multiple real-time [10].

For completeness, we recall the definition of the Nagel–Schreckenberg model for single-lane traffic. The road is subdivided into cells (see Fig. 1). Each cell is either empty or occupied by only one vehicle with a discrete velocity $v \in \{0, \ldots, v_{\max}\}$, $v_{\max}$ being the maximum velocity. The dynamics of the vehicles is described by the following rules (parallel update):

1. Acceleration and braking $v' \leftarrow \min(v + 1, v_{\max}, g)$.
2. Randomisation $v'' \leftarrow \max(0, v' - 1)$ with probability p.
3. Driving $x' \leftarrow x + v''$.

A time step corresponds to $\Delta t = 1$ second, the typical time a driver needs to react. With a maximum velocity of $v_{\max} = 5$ cells/time step, the cars can speed up to 135 km/h. The first rule describes an optimal driving strategy: *Drive as fast as you can and slow down if you have to!* The stochastic parameter p mimics the complex interactions between the vehicles and is responsible for the spontaneous formation of jams. The rules for single-lane traffic can easily be expanded to describe multi-lane traffic and complex intersections [3,8].

2.2. Road network and traffic data

Although urban road networks are very complex, arbitrary kinds of roads and intersections can be constructed with only a few basic elements [3]. In this manner, the road network of Duisburg was mapped, an area of 30 km^2. It consists of 107 nodes (61 signalised, 22 non-signalised and 24 boundary nodes), 280 edges and 22,059 cells corresponding to 165 km. The boundary nodes are the sources or sinks of the system.

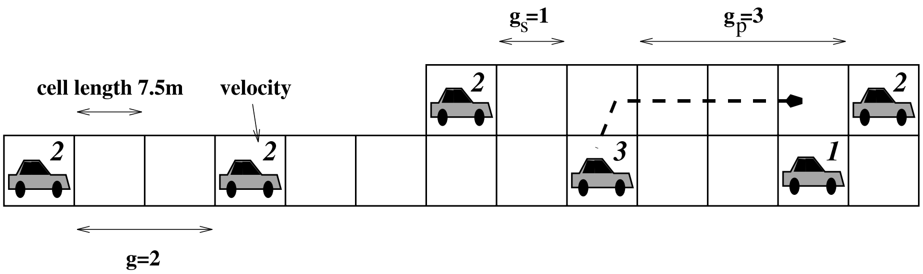

Fig. 1. Part of a road in the Nagel–Schreckenberg model. The road is subdivided into cells, which are 7.5 m long. Each car has a discrete velocity v which is restricted by the headway g. For a safe lane change two more gaps, g_s and g_p, have to be taken into account (see dashed line).

For an on-line simulation, the model is supplemented by traffic data stemming from 750 inductive loops. The data (approx. 4 kB/min.) are sent by the municipal authority of Duisburg. These data are used to calculate turning probabilities and to tune the simulation at the measure points. Since origin–destination matrices with a sufficient temporal and spatial resolution are hardly available, vehicles are driven randomly through the network. Thus, the cars do not follow predefined routes, instead they choose their way at every node according to a turning probability.

The traffic state of the whole network can be calculated 350 times faster than real-time on an ordinary Pentium 400 MHz, i.e., the traffic of a whole day can be calculated in 5 minutes. The results are published in the Internet every minute [9]. In the next section, we show how these data can be processed in an ATIS.

3. Fuzzy route guidance system

From a mathematical point of view, the problem of determining an optimal route in a traffic network can be described as a multiple criteria optimisation problem on a graph with time-dependent arc costs (see, e.g., [5]). Even though the quality of the routes with respect to a single criterion can be determined quite simply, it is not obvious how to describe the optimality of routes when different criteria are considered and how to determine the optimal solution in that case.

Standard optimisation models on graphs use linear cost functions to model the significance of different criteria. This method is very effective in the sense that it is easy to compute the 'optimal' route and the criterion that is weighted the most is always heavily stressed. On the other hand, these models tend to ignore the concept of the diminishing marginal utility, i.e., linear cost functions tend to overemphasise the most weighted criteria. For example, a route guidance system with linear costs would often sacrifice most of the comfort of driving on less frequented streets to save the 5 seconds of travel time that were missing to hit the optimal travel time. In the following subsection, a fuzzy decision model which is based on the symmetric decision model by Bellman and Zadeh [2] is presented. The next subsection describes its application to a routing model including a specification of the employed fuzzy sets. The last part presents some of the results obtained by the comparison with the case of linear cost functions.

3.1. Symmetric optimisation

This section is devoted to symmetric optimisation. The application of symmetric optimisation to the problem of routing vehicles is explained in three subsections. First, the underlying decision model is explained. Then, the problem of weighting fuzzy criteria is briefly outlined and the weights that were used in the research are defined. Finally, the model is applied to routing problems.

3.1.1. Decision model

In [2] a symmetric optimisation model is suggested to describe multiple criteria optimisation problems involving the absence of sharply defined criteria. The model is based on fuzzy set theory which was first introduced in [14]. For detailed information about fuzzy set theory, the reader is referred to [6,11,15–17]. We present a short description of the symmetric optimisation model. It consists of the following components:

- a finite set $\mathbf{A}$ of alternatives,
- a finite set $\mathbf{C}$ of constraints, and
- a finite set $\mathbf{O}$ of objective functions which evaluates a decision $a \in \mathbf{A}$.

The basic notion of the symmetric decision model is to express constraints $C \in \mathbf{C}$ and objectives $O \in \mathbf{O}$ by fuzzy sets, which are usually called *fuzzy criteria*. Fuzzy sets can be associated with a function $D : X \to [0, 1]$ defined on a universe X. Let $\mathbf{F}(g \cdot \beta X)$ be the set of all fuzzy sets defined on the universe X. The fuzzy criteria have the following properties: An alternative $a_1 \in \mathbf{A}$ is better than an alternative $a_2 \in \mathbf{A}$ with respect to a fuzzy criteria $F \in \mathbf{F}(\mathbf{A})$, if and only if $F(a_1) \geqslant F(a_2)$. In order to combine different fuzzy criteria, generalised intersection operators $t : [0, 1] \times [0, 1] \to [0, 1]$ can be used. Using this, the *fuzzy decision* $D \in \mathbf{F}(\mathbf{A})$ assesses the quality of an alternative $a \in \mathbf{A}$, where D is defined as

$$D(a) := t(C_1(a), t(C_2(a), \ldots, t(C_{n-1}(a), C_n(a)))\ldots))) \quad (1)$$

with the fuzzy criteria $C_1, \ldots, C_n \in \mathbf{F}(\mathbf{A})$. Then, the solution $a^* \in \mathbf{A}$ of the optimisation problem

$$D(a^*) = \max_{a \in \mathbf{A}} D(a), \quad (2)$$

is an *optimal alternative* with respect to the fuzzy decision D. Because constraints C and objectives O are treated in the same way, the decision model (2) is called symmetric. In fuzzy set theory introduced by Zadeh, there are various intersection operators which claim to model human decision making. For example, the algebraic product $t(a, b) := a \cdot b$ is important in fuzzy decision theory.

3.1.2. Weighting of fuzzy criteria

Yager [13] suggested a method for weighting fuzzy criteria in the decision model (2), if the decision maker is able to express the importance of the criteria by weights

$$\omega_1, \ldots, \omega_n \geqslant 0 \quad \text{with} \quad \sum_{i=1}^{n} \omega_i = n. \quad (3)$$

If ω_i is the weight of the ith fuzzy criterion C_i, then this criteria is weighted exponentially by $[C_i]^{\omega_i}$ in the fuzzy decision D (see (1)).

3.1.3. Fuzzy routing model

Consider a directed graph $\vec{G} = (V, E)$ with a starting point $s \in V$ and a destination $d \in V$. Let A be the set of all acyclic routes from point s to point d on $\vec{G} = (V, E)$. On each arc $a \in E$, n criteria are defined. A multi-criteria structure is superimposed on the graph as follows: associated with each arc $a \in E$ are arc costs $k_a^i \geqslant 0, i = 1, \ldots, n$ for each criterion. The cost of a path $r \in A$ with respect to the ith criterion is then defined as the sum of all arc costs k_a^i of the path r with respect to the ith criterion. Furthermore, we denote these costs of a path r by $\Pi_i(r)$, where $\Pi_i : A \to \mathbb{R}_+$ is a projection for all $i = 1, \ldots, n$. In order to measure the 'optimality' of a path $r \in A$ for the ith criterion, we define the function

$$\alpha_i : A \to [1, \infty) \quad \text{with} \quad \alpha_i(r) := \frac{\Pi_i(r)}{\min_{\tilde{r} \in A} \Pi_i(\tilde{r})} \quad (4)$$

for all $i = 1, \ldots, n$. For example, if $\alpha_i(r) = 1.5$, then r is 50% worse than the optimal route from s to d with respect to the ith criterion. The quality of each route r is then given by the fuzzy decision $D \in \mathbf{F}(A)$ defined by

$$D(r) := t([C_1(r)]^{\omega_1}, t([C_2(r)]^{\omega_2}, \ldots, t([C_{n-1}(r)]^{\omega_{n-1}}, [C_n(r)]^{\omega_n}))\ldots))) \quad (5)$$

with the monotonically decreasing fuzzy criteria $C_1, C_2, \ldots, C_n \in \mathbf{F}(A)$, the weights $\omega_1, \ldots, \omega_n$ in (3) and an intersection operator t. Furthermore, we assume $C_1(1) = \cdots = C_n(1) = 1$. Our objective is then to solve the optimisation problem (2) with the fuzzy decision D in (5).

3.2. Application of the fuzzy routing model

This subsection is concerned with the application of the symmetric decision model (2) to route guidance systems. The data are provided by the on-line simulation described in Section 2.

3.2.1. Objectives

The input for the decision D in (5) depends on the specific criterion used. In our case the four criteria, which are described below, were used to cover the drivers' preferences. Basically, road users want to get as fast as possible to their destination, but not at any cost. They are also interested in convenient transportation which is taken into account by several other criteria. We used two dynamic and two static arc costs:

- *Dynamic arc costs*:
  - Travel time: determined on every arc on-line.
  - Traffic density: an aspect of convenient driving.
- *Static arc costs*:
  - Road type: streets are classified into arterial roads and regular streets.
  - Route length: note that the shortest path is not always the fastest.

Generally, it is difficult to determine an 'optimal' route since there is a high degree of subjectivity

involved. For example, wide roads with low-traffic density are usually perceived to be faster than other ones, even if they are not, as the mere feeling of 'getting somewhere' is satisfying to a driver.

3.2.2. Choice of fuzzy sets

The next question that arises is how to represent the underlying fuzzy criteria by a choice of suitable fuzzy sets. For modelling utility, psychological research suggests using S-shaped functions. One of their main advantages lies in the fact that (when suitable parameters are used) the increase in utility near the optimum is very small compared to linear utility functions. This fact corresponds to the concept of the diminishing marginal utility. In our case, all fuzzy criteria were modelled by the following functions $G_{(D,B)}$ defined by

$$G_{(D,B)}(x) := \begin{cases} \frac{\Phi_B^D(x)}{\Phi_B^D(1)} & x \geqslant 1, \\ 1 & x \in [0,1). \end{cases} \tag{6}$$

The underlying functions Φ_B^D that produce the curves are defined for parameters $B \in \mathbb{R}_+, D > 1$ as follows:

$$\Phi_B^D(x) := \frac{1}{2}(1 - \tanh(10 \cdot B \cdot (x - D))). \tag{7}$$

The parameter D determines the point x, where $G''_{(D,B)}(x) = 0$ and the parameter B induces the curvature of the function. Fig. 2 shows the function $G_{(D,B)}$ with parameters $D = 1.4$ and $B = 0.34$.

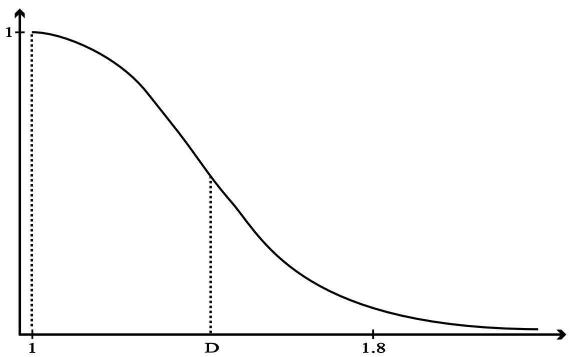

Fig. 2. Fuzzy set. Note that the concept of the diminishing marginal utility is included.

3.3. Results

3.3.1. Heuristic to compute approximate solutions

The problem of determining exact solutions of the fuzzy routing model represents a non-linear optimisation model. For this case, it is easy to show that not every optimal path of the decision model needs to be composed of optimal subpaths. Hence, Bellman's principle of optimality [1], which ensures the correctness of all efficient shortest path algorithms, does not hold. In order to demonstrate the advantages of decisions based on the fuzzy routing model, we compute approximate solutions. We present a non-polynomial method for generating a set $S^* \subseteq A$ of approximate solutions: consider the linear cost function

$$U : A \to \mathbb{R}_+; \text{ defined by } U(r) := \sum_{i=1}^{4} \alpha_i(r) \cdot \omega_i, \tag{8}$$

where $\omega_1, \ldots, \omega_4$ denote the weights of the four fuzzy criteria (see (3)) and A the set of all acyclic paths from starting point s to destination point d. Using this, we compute the constant $K := \min\{U(r) | r \in A\}$ by using Dijkstra's shortest path algorithm. To compute an approximate solution of the fuzzy routing model, we search for a solution $r^* \in S^*$ of the optimisation problem

$$D(r^*) = \max_{r \in S^*} D(r) \tag{9}$$

with $S^* := \{r \in A | U(r) \leqslant K \cdot \delta\}$, a fixed constant $\delta > 1$ and the fuzzy decision D in (5). In our approach we set $\delta = 1.8$.

3.3.2. Quality of the model and comparison with the linear case

To test the quality of the model, two series of experiments are performed using data stemming from the on-line simulation and their results were compared to the case of linear optimisation. It was found that the fuzzy sets were facilely calibrated concerning their emphasis on the most weighted criteria, i.e., by choosing suitable values for D and B (see Section 3.2.2) the desired preference behaviour of the model could be implemented.

The most important ability of the fuzzy routing model is to compromise between different preferences. The first series of results (see Tables 1 and 2) leads to the experience that the model is capable of compromising between heavily weighted criteria and those of minor importance. For example: Similar to human beings, the fuzzy model does not accept driving twice the distance to save 5 seconds of travel time, even if travel time is the major criterion. The second series (see Tables 3 and 4) proved the models capability to find balanced solutions in a case, where two contrary criteria like travel time and road type are evenly preferred. In that case, linear models tend to arbitrarily favour one criterion and 'neglect' the other one.

In order to combine the four fuzzy criteria, we used the algebraic product as intersection operator, whereas all fuzzy criteria in (5) were represented by the fuzzy set of the type $G_{(1.4,0.34)}$. In the first example we used three routes. Table 1 indicates the strong emphasis that the linear model puts on the major objective. For example, the linear optimisation model accepts in r_2 a travel distance that is more than twice as long as the optimum. Moreover, the criterion *road type* is completely ignored. On the other hand, Table 2 illustrates that the preference behaviour of the fuzzy model is much more balanced. It will be satisfied with values nearby the optimum value for α_{traffic} so that the other criteria are met as well.

The importance of compromising between different criteria increases when contrary criteria are equally heavily weighted. This ability is demonstrated in Tables 3 and 4 for two routes.

Table 1
Results for the linear cost function for three different paths with $\omega_{\text{traffic}} = 3$ and $\omega_{\text{time}} = \omega_{\text{road}} = \omega_{\text{length}} = 0.33$

Paths	$\alpha_{\text{length}}(r_i)$	$\alpha_{\text{time}}(r_i)$	$\alpha_{\text{traffic}}(r_i)$	$\alpha_{\text{road}}(r_i)$
r_1	1.65	1.16	1.03	2.69
r_2	2.05	1.15	1	3.92
r_3	1.27	2.76	1	1.16

Table 2
Results for the fuzzy decision model (parameters see Table 1)

Paths	$\alpha_{\text{length}}(r_i)$	$\alpha_{\text{time}}(r_i)$	$\alpha_{\text{traffic}}(r_i)$	$\alpha_{\text{road}}(r_i)$
r_1	1.44	1.07	1.11	2.32
r_2	1.4	1	1.3	1.75
r_3	1.13	1.08	1.43	1.8

Table 3
Results for the linear cost function for two different paths with $\omega_{\text{traffic}} = \omega_{\text{road}} = 1.81$ and $\omega_{\text{time}} = \omega_{\text{length}} = 0.181$

Paths	$\alpha_{\text{length}}(r_i)$	$\alpha_{\text{time}}(r_i)$	$\alpha_{\text{traffic}}(r_i)$	$\alpha_{\text{road}}(r_i)$
r_1	1	1.92	1.81	1
r_2	1	1.09	1.91	1.14

Table 4
Results for the fuzzy decision model (parameters see Table 3)

Paths	$\alpha_{\text{length}}(r_i)$	$\alpha_{\text{time}}(r_i)$	$\alpha_{\text{traffic}}(r_i)$	$\alpha_{\text{road}}(r_i)$
r_1	1.11	1.41	1.53	1.65
r_2	1.12	1.12	1.74	1.36

4. Summary and outlook

We presented an ATIS, which is based on dynamic data provided on-line by a simulation supplemented by real traffic data [9]. With regard to different preferences, a road user can choose an optimal trip. This multi-criteria optimisation problem is solved employing the symmetric decision model proposed by Bellmann and Zadeh. We have compared the fuzzy routing model to a model with a linear cost function for two different cases: One criterion is heavily weighted and two contrary criteria which are weighted evenly. In both cases, the fuzzy routing model found a good compromise between the different criteria, whereas the linear model tends to overestimate one criterion and neglect the others. This is due to the fact that the concept of the diminishing marginal utility is not incorporated.

In the future, we will present this system in the Internet giving the road user the opportunity to find an optimal trip with regard to the actual traffic state.

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